Information retrieval in an infodemic: the case of COVID-19 publications

Douglas Teodoro, Sohrab Ferdowsi, Nikolay Borissov, Elham Kashani, David Vicente Alvarez, Jenny Copara, Racha Gouareb, Nona Naderi, Poorya Amini

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Douglas Teodoro[1, 2*] PhD; Sohrab Ferdowsi[1*] PhD; Nikolay Borissov[3, 4] PhD; Elham Kashani[5] MSc; David Vicente Alvarez[1] BSc; Jenny Copara[1, 2, 6] MSc; Racha Gouareb[1] PhD; Nona Naderi[1, 2] PhD; Poorya Amini[3, 4] PhD

[1]HES-SO University of Applied Arts and Sciences of Western Switzerland Carouge CH
[2]SIB Swiss Institute of Bioinformatics Lausanne CH
[3]Risklick AG Bern CH
[4]Clinical Trials Unit Bern Bern CH
[5]Institute of Pathology University of Bern Bern CH
[6]University of Geneva Geneva CH
[*]these authors contributed equally

Corresponding Author:
Douglas Teodoro PhD
HES-SO University of Applied Arts and Sciences of Western Switzerland
Rue de la Tambourine 17
Carouge
CH

Abstract

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Information retrieval in an infodemic: the case of COVID-19 publications

Douglas Teodoro[1,2,3,*,+], Sohrab Ferdowsi[1,2+], Nikolay Borissov[4,5], Elham Kashani[6], David Vicente Alvarez[1], Jenny Copara[1,2,3], Racha Gouareb[1,2], Nona Naderi[1,3], Poorya Amini[4,5]

[1] HES-SO University of Applied Sciences and Arts of Western Switzerland, Carouge, CH-1227, Switzerland

[2] University of Geneva, Geneva, CH-1205, Switzerland

[3] SIB Swiss Institute of Bioinformatics, Lausanne, CH-1015, Switzerland

[4] Risklick AG, Bern, CH-3013, Switzerland

[5] Clinical Trials Unit Bern, Bern, CH-3012, Switzerland

[6] University of Bern, Institute of Pathology, Bern, CH-3008, Switzerland

[*]douglas.teodoro@unige.ch

[+] these authors contributed equally to this work

Abstract

Background: The coronavirus disease (COVID-19) global health crisis has led to an exponential surge in the published scientific literature. In the attempt to tackle the pandemic, extremely large COVID-19-related corpora are being created, sometimes with inaccurate information, which is no longer at scale of human analyses.
Objective: In the context of searching for scientific evidence in the deluge of COVID-19-related literature, we present an information retrieval methodology for effective identification of relevant sources to answer biomedical queries posed using natural language.
Methods: Our multi-stage retrieval methodology combines probabilistic weighting models and re-ranking algorithms based on deep neural architectures to boost the ranking of relevant documents. Similarity of COVID-19 queries are compared to documents and a series of post-processing methods are applied to the initial ranking list to improve the match between the query and the biomedical information source and boost the position of relevant documents.
Results: The methodology was evaluated in the context of the TREC-COVID challenge, achieving competitive results with the top-ranking teams participating in the competition. Particularly, the combination of bag-of-words and deep neural language models significantly outperformed a BM25-based baseline, retrieving on average 83% of relevant documents in the top 20.
Conclusions: These results indicate that multi-stage retrieval supported by deep learning could enhance identification of literature for COVID-19-related questions posed using natural language.

Keywords information retrieval; multi-stage retrieval; neural search; deep learning; COVID-19; coronavirus; infodemic; infodemiology; literature; online information;

Introduction

In parallel to its public health crisis with vast social and economic impacts, the coronavirus disease (COVID-19) pandemic has resulted in an explosive surge of activities within scientific communities and across many disciplines [1]. In turn, it has led to an overabundance of information online and offline - a phenomenon described as infodemic [2–4]- with often negative impact on the population [5]. Since early 2020 when the pandemic was officially announced, the number of publications related to COVID-19 has had an exponential growth [6]. In addition to the volume and velocity of the generated data, the heterogeneity as a result of the typical variety of concept naming found in the biomedical field, spelling mistakes, and the different source types [7] make searching and discovery of relevant literature within the COVID-19 corpora an important challenge [2].

With the sheer quantity of COVID-19 information continuously produced, researchers, policy makers, journalists, and ordinary citizens, among others, are unable to keep up with fast evolving body of knowledge disseminated. As knowledge about the pandemic evolves, study results and conclusions may be improved, contradicted or even proven wrong [3]. Combined with a relentless media coverage and social media interactions, this fast changing and massive amount of information leads to confusion and desensitization among audiences, e.g., as in the case of school opening guidelines and mask-wearing and social distancing recommendations [5,8]. They also fuel deliberate attempts to create information disorders, such as misinformation, disinformation, mal-information and fake-news [9], reducing the effectiveness of public health measures and endangering countries' ability to stop the pandemic, ultimately having a negative impact in live costs [10,11].

To support states and relevant actors of society to manage the COVID-19 infodemic, the WHO has published a framework containing 50 recommendations, of which more than 20% are related to strengthening the scanning, review and verification of evidence and information [2]. To help actors involved with the pandemic find the most relevant information for their needs, effective information retrieval models for the COVID-19-related corpora became thus a prominent necessity [12]. The information retrieval community, in turn, has responded actively and quickly to this extraordinary situation and has been aiming at addressing these challenges. To foster research for the scientific communities involved with the pandemic, the COVID-19 Open Research Dataset (CORD-19) [13] collection was built to maintain all the related publications to the family of coronaviruses. This dataset helped research in various directions and several tasks are built around it, including natural language processing (NLP) related tasks, like question answering [14] and language model pre-training [15], and information retrieval challenges in Kaggle [16] as well as the TREC-COVID [17,18].

The TREC-COVID [18–20] challenge ran in 5 rounds, each asking for an incremental set of information needs to be retrieved from publications of the CORD-19 collection. In a TREC-COVID round, participants were asked to rank documents of the CORD-19 corpus in decreasing order of likelihood of containing answers to a set of query topics. At the end of the round, experts provided relevance judgements for the top ranking documents submitted by different participants using a pooling strategy [21]. Although limited to the first several top submissions of the participating teams, these relevance judgements enable the evaluation of the different models and are valuable examples to train retrieval models for the subsequent rounds of the challenge.

To improve search and discovery of COVID-19 scientific literature, in this work we aim to investigate an information retrieval model supported by deep language models to enhance findability of relevant documents in fast evolving corpora.
More than 50 teams participated in the TREC-COVID challenge worldwide, developing new

information retrieval and NLP methodologies to tackle this complex task [22–27]. Having participated in the TREC-COVID challenge, in this paper we detail our retrieval methodology, which brought us competitive results with the top-ranking teams. Particularly, we use a multi-stage retrieval pipeline, combining classic probabilistic weighting models with novel learning to rank approaches made by ensemble of deep masked language models. We present our results and analyse how the different components of the pipeline contribute to providing the best answers to the query topics.

Related work

Two-stage information retrieval

Currently, two main methodologies are used to rank documents in information retrieval systems: *i)* the classic query-document probabilistic approaches, such as BM25 [28] and probabilistic language models [29], and *ii)* the learning-to-rank approaches, which usually post-process results provided by classic systems to improve the original ranked list [30,31]. When there are sufficient training data, i.e., queries with relevance judgements for the case of information retrieval, learning-to-rank models often outperform classic one-stage retrieval systems [30,32]. Nevertheless, empiric results have also shown that the re-ranking step may degrade the performance of the original rank [33]. Progress on learning-to-rank algorithms have been fostered thanks to the public release of annotated benchmark datasets, such as the LETOR [34] and the Microsoft Machine Reading Comprehension (MS MARCO) [35].

Learning-to-rank approaches can be categorised into three main classes of algorithms - pointwise, pairwise and listwise - based on whether they consider one document, a pair of documents or the whole ranking list in the learning loss function, respectively [30–32,36]. Variations of these learning-to-rank algorithms are available based on neural networks [31,36] and other learning algorithms, such as boosting trees [37]. More recently, pointwise methods leveraging the power of neural-based masked language models have attracted great attention [38,39]. These learning-to-rank models use the query and document learning representations provided by the masked language model to classify whether a document in the ranked list is relevant to query. While these two-stage retrieval methods based on neural re-rankers provide interesting features, such as learned word proximity, in practice, the first stage based on classic probabilistic retrieval algorithms is indispensable, as the algorithmic complexity of the re-ranking methods makes them often prohibitive to classify the whole collection [32].

Recent advances in text analytics, including question answering, text classification and information retrieval, have indeed mostly been driven by neural-based masked language models. A seminal effort in this direction is the Bidirectional Encoder Representations from Transformers (BERT) model [38], which shows significant success in a wide range of NLP tasks. BERT uses a bi-directional learning approach based on the transformer architecture [40] and is trained to predict masked words in a context. Since the introduction of BERT, several works tried to augment its performance. A successful work in this direction is RoBERTa [41], using larger and more diverse corpora for training as well as a different tokenizer. While RoBERTa needs larger computing power, it often improves the performance of BERT across different downstream tasks. Another similar effort is the XLNet model [42], which uses a permutation-based masking, showing also consistent improvement over BERT.

TREC-COVID retrieval efforts

Recently, the specific case of retrieval of COVID-related scientific publications has been addressed in several efforts [22–27]. These works follow mostly the above two-stage retrieval process. Among the first efforts is the SLEDGE system [22], where the authors detail their solutions for the first round of TREC-COVID challenge using a BM25-based ranking method followed by a neural re-

ranker. An important difficulty for the first round of the challenge is the absence of labelled data. To overcome this limitation, the authors lightly tune the hyper-parameters of the first stage ranking model using minimal human judgements on a subset of the topics. As for the second stage, they use the SciBERT model [43], which is pre-trained on biomedical texts, and fine-tuned on the general MS MARCO set [35] with a simple cross-entropy loss. CO-Search [24] uses a slightly different approach, wherein they incorporate semantic information, as captured by Sentence-BERT [44], also within the initial retrieval stage. Moreover, they use the citation information of publications in their ranking pipeline. In the work of Covidex [23], the authors provide a full-stack search engine implementing a multi-stage ranking pipeline, where their first stage is based on the Anserini information retrieval toolkit [45], complemented by different neural re-ranking strategies. They address the issue of length variability among documents with an atomic document representation using, for example, paragraph-level indexing.

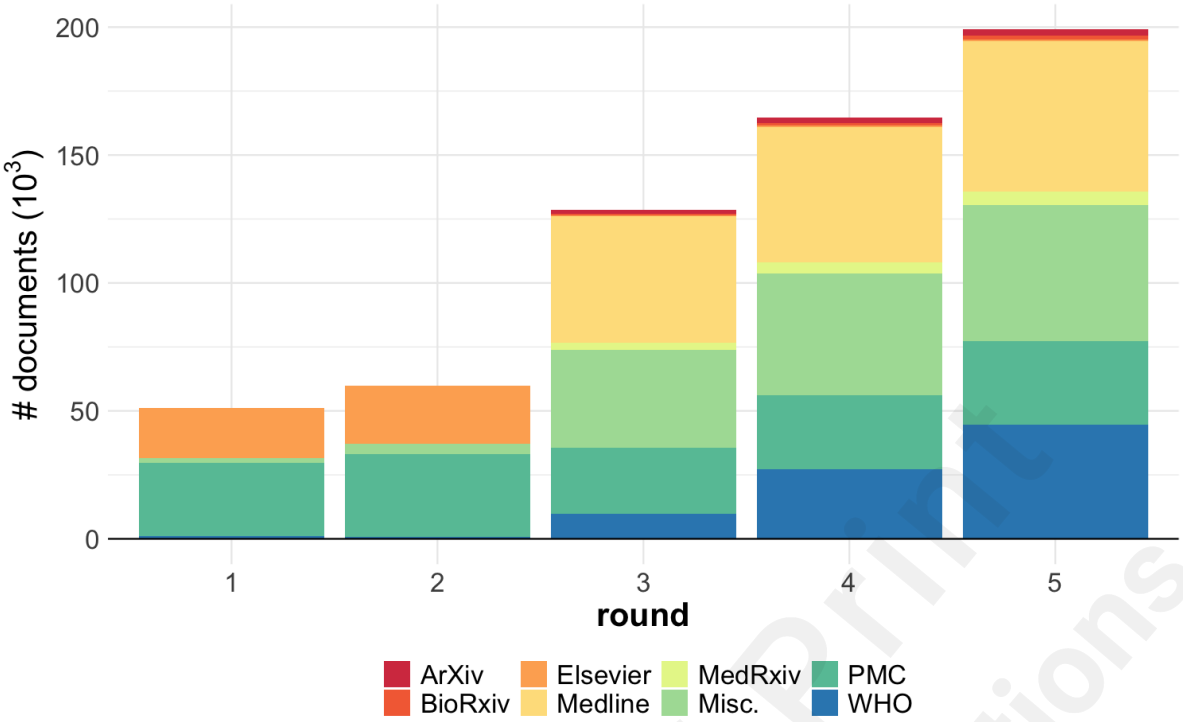
Methods

In this section, we describe the corpus and query set, and our methodology for searching COVID-19 related literature in the context of the TREC-COVID challenge. We start by introducing the CORD-19 dataset, which is the corpus used in the competition. We then describe the challenge organisation and assessment queries. Then, we detail our searching methodology, based on multi-stage retrieval approach. Finally, we present the evaluation criteria used to score the participants' submissions. For further details on the TREC-COVID challenge, see [19,20].

The CORD-19 dataset

A prominent effort to gather publications, preprints and reports related to the coronaviruses and acute respiratory syndromes (COVID-19, MERS and SARS) is the CORD-19 collection of the Allen Institute for Artificial Intelligence (in collaboration with other partners) [13]. (Figure 1) describes the size and content origin of the corpus for the different TREC-COVID rounds. As we can see, this is a large and dynamically growing semi-structured dataset from various sources like PubMed, PubMed Central, WHO and preprint servers like bioRxiv, medRxiv, and arXiv. The dataset contains document metadata, including *title*, *abstract*, *authors*, among others, but also the full text or link to full text files when available. A diverse set of related disciplines, e.g., from virology and immunology to genetics, are represented in the collection. Throughout the challenge, the dataset was updated daily and snapshot versions representing its status at a certain time were provided to the participants for each round. In the last round of the TREC-COVID challenge, the corpus contained around 200'000 documents, coming mostly from Medline, PMC and WHO sources.

Figure 1. Evolution of the CORD-19 corpus across the TREC-COVID rounds stratified by source.



The TREC-COVID challenge

To assess the different information retrieval models, the TREC-COVID challenge provided a query set capturing relevant search questions of researchers during the pandemic. These needs are stated in query topics, consisting of three free text fields - *query*, *question* and *narrative* - with an increasing level of context, as shown in the example of (Table 1). The challenge started with 30 topics in round 1 and added five new topics at each new round, reaching thus 50 topics in round 5.

Table 1. Examples of a TREC-COVID topics with the fields *query*, *question* and *narrative*.

topic	query	question	narrative
1	coronavirus origin	what is the origin of COVID-19?	seeking range of information about the SARS-CoV-2 virus's origin, including its evolution, animal source, and first transmission into humans.
25	coronavirus biomarkers	which biomarkers predict the severe clinical course of 2019-nCOV infection?	Looking for information on biomarkers that predict disease outcomes in people infected with coronavirus, specifically those that predict severe and fatal outcomes.
50	mRNA vaccine coronavirus	what is known about an mRNA vaccine for the SARS-CoV-2 virus?	Looking for studies specifically focusing on mRNA vaccines for COVID-19, including how mRNA vaccines work, why they are promising, and any results from actual clinical studies.

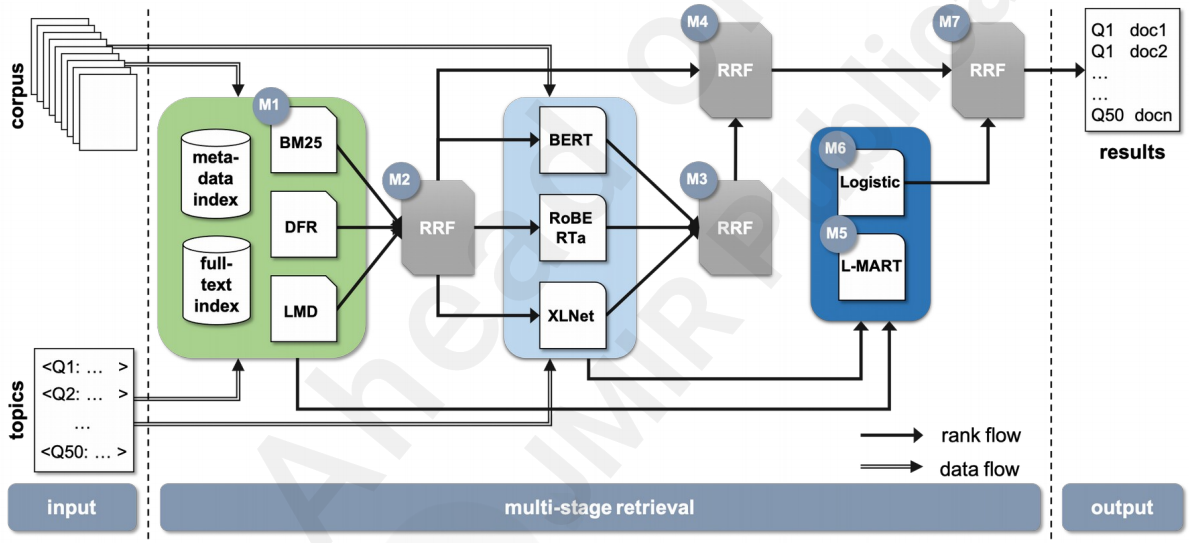
In each round, the participants provided ranked lists of candidate publications of the CORD-19 collection, which best answered the query topics. Each list was generated by a different information retrieval model, so called *run*, with up to 5 runs in the first 4 rounds and 7 runs in the last round per

team. At the end of the round, domain experts examined the top k candidate publications (where k is defined by the organisers) from the priority runs of the teams and judged them as “highly relevant”, “somehow relevant”, or “irrelevant”. Then, based on the consolidated relevance judgements, the participants were evaluated using standard information retrieval metrics (NDCG, precision, etc.). Judged documents for a specific topic from previous rounds were excluded from the relevance judgement list.

Proposed multi-stage retrieval methodology

(Figure 2) shows the different components of our information retrieval pipeline for the COVID-related literature. These components can be divided into three main categories: *i)* first-stage retrieval using classic probabilistic methods; *ii)* second-stage (neural) re-ranking models; and *iii)* rank fusion algorithms. Given a corpus containing metadata information, such as title and abstract, and full text, when available, documents are stored using directed and inverted indexes. Then, transformer-based and classic learning-to-rank models trained using relevance judgements are used to classify and re-rank pairs of query-document answers. The ranked list obtained from the different models are further combined using the reciprocal rank fusion (RRF) algorithm.

Figure 2. Multi-stage retrieval pipeline. Light green: first-stage retrieval. Light and dark blue: second-stage retrieval. M1-M7 denote the different models to create the respective runs 1-7 in round 5. RRF: Reciprocal Rank Fusion. Logistic: logistic regression model. L-MART: LambdaMART model.



First-stage retrieval

For the first-stage retrieval, we assessed three variations of the classic query-document probabilistic weighting models: Okapi Best Match 25 (BM25) [46], Divergence from Randomness (DFR) [47] and Language Model Dirichlet (LMD) [48].

Okapi Best Match 25: Our first classical model, Okapi BM25 [28], is based on the popular term frequency-inverse document frequency (tf-idf) framework. In the tf-idf framework, term weights are calculated using the product of within term-frequency tf and the inverse document frequency idf statistics. Denote $f(t,d)$ as the number of times a term t appears in a document d within a collection D, BM25 calculates the term-weight w as:

$$w(t,d,D) \propto tf(t,d) \cdot idf(t,D)$$

where $|d|$ is the length of the document, $|D|$ is the size of the collection, avg_l is the average length of the documents in the collection, n_t is the number of documents containing the term t, and k_1 and b are parameters of the model associated with the term frequency and the document size normalisation, respectively.

Divergence from Randomness: The second model, DFR, extends the basic tf-idf concept by considering that the more the divergence of the term-frequency tf from its collection frequency cf ($cf \approx df$), the more the information carried by the term in the document [47]. Thus, for a given model of randomness M, in the DFR framework the term-weight is inversely proportional to the probability of term-frequency within the document obtained by M for the collection D:

$w(t,d,D) = k \cdot \log p_M(t \in d|D)$,

where p_M is a probabilistic model, such as binomial or geometric distributions, and k is a parameter of the probabilistic model.

Language Model Dirichlet: The third model, LMD, uses a language model, which assigns probabilities to word sequences, with a Dirichlet-prior smoothing, to measure the similarity between a query and a document [48]. In a retrieval context, a language model specifies the probability that a document is generated by a query, and smoothing is used to avoid zero probabilities to unseen words and improves the overall word probability accuracy. In the LMD algorithm, term-weigh is calculated using the following equation:

$$w(t,d,D) = \frac{|d|}{|d|+\mu} \cdot p(t|d) + \frac{\mu}{|d|+\mu} \cdot p(t|D),$$

where $p(t \vee d)$ denotes the probability of a term in a document, $p(t \vee D)$ is the probability of a term in the collection, and μ is the Dirichlet parameter to control the amount of smoothing.

In our pipeline, the BM25, DFR and LMD implementations are based on the Elasticsearch framework. The model parameters were trained using the relevance judgements of the round 4 in a 5-fold cross-validation setup.

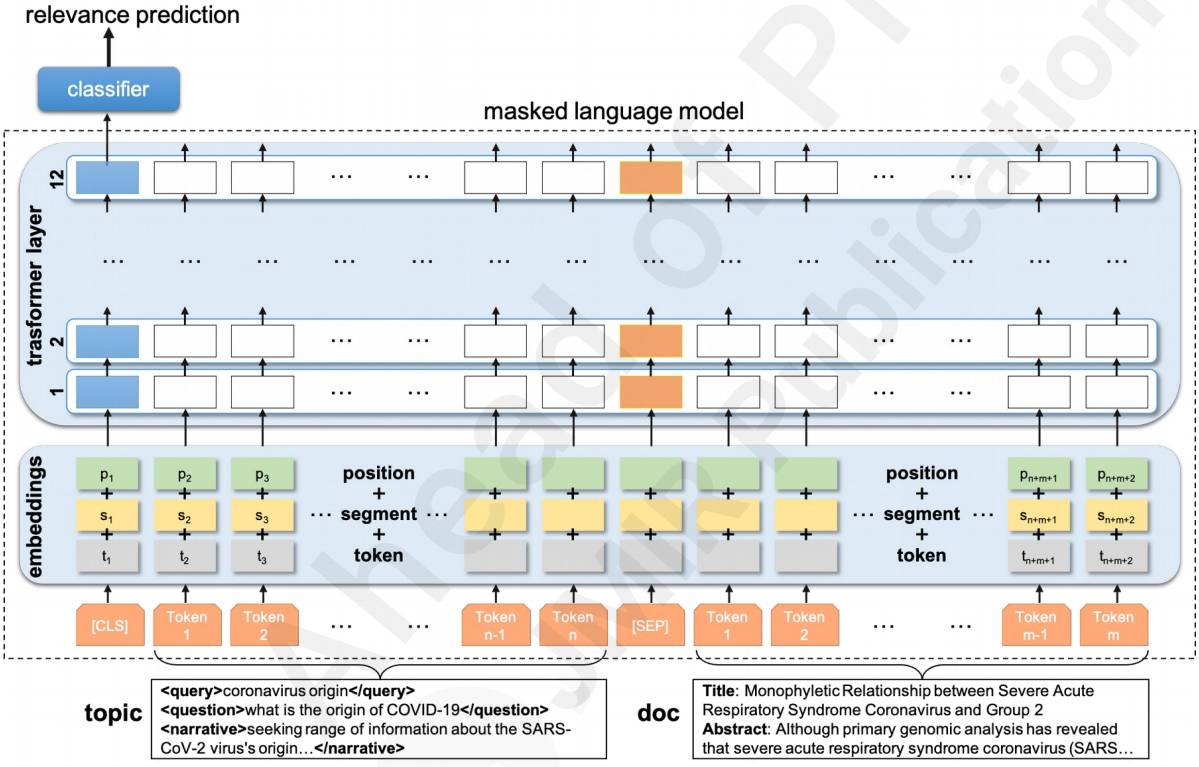
Second-stage re-ranking

The models used in the first-stage ranking are based on the bag-of-words statistics, where essentially we look at the histogram of query terms, and their document and collection statistics but neglect the sequential nature of text and word relations. To mitigate these limitations and improve the initial rankings, after the first-stage retrieval, we use neural masked language models trained on the relevance judgements from previous rounds so that syntactic and semantic relations can be better captured [49,50]. As shown in (Figure 2), we assessed three masked language models based on the transformer architecture: BERT, RoBERTa and XLNet.

BERT: (Figure 3) shows the general idea of how we use the BERT language model to match documents to a query topic. Given a topic and a document associated to it as input and a relevance judgement as the label for the query-document association (relevant or not), the model is trained or fine-tuned in the BERTology parlance, as it had been previously pre-trained on a large corpus, to predict whether the document is relevant or not to the query. In the input layer of the pre-trained model, the topic and candidate publication are tokenized and separated by the language model *[SEP]* token (stands for sentence separation). Moreover, to enforce the sequential structure of text, positional embedding as well as sentence embedding are added to the main embeddings for each token. These embeddings are then fed to the transformer layers of BERT, which are updated during the fine-tuning step. Finally, the output of the special *[CLS]* token (stands for classification) is used to determine the relevance of the candidate publication to the queried information topic.

Using the query topics from a preceding round (round 4 for the results presented here) and their respective list of relevance judgements, we fine-tuned the BERT model to re-score the initial association of the query-document pair between 0 (not relevant) and 1 (very relevant). For this, we use the score associated to the *[CLS]* token position. We limit the input size of the query and document to 512 tokens (or sub-words). Then, at the second-stage re-ranking step we classify the top k publications retrieved by the first stage models using the fine-tuned BERT model (we set $k=5000$ in our experiments).

Figure 3. Neural masked language model for document relevance classification. As inputs to the pre-trained masked language model, the topics and candidate publications are separated by the [SEP] tag. Inputs are tokenized using sub-words tokenization methods (grey boxes). Segment embeddings (yellow boxes) represent the difference between a topic and a document input. Position embeddings (green boxes) enforce the sequential structure of text. The transformer and classification layers are updated in the training phase using the relevance judgements. The output of the special [CLS] token is finally used to determine the relevance of the candidate publication to the queried information topic.



RoBERTa and XLNet: Identical training strategies were used for the RoBERTa and XLNet language models. The main difference for the RoBERTa model is that it was originally pre-trained on a corpus with an order of magnitude bigger compared to BERT (160GB *vs.* 16GB). Moreover, it uses dynamic masking during the training process, that is, at each training epoch, the model sees different versions of the same sentence with masks on different positions, compared to a static mask algorithm for BERT. Lastly, RoBERTa uses a byte-level Byte-Pair-Encoding tokenizer compared to BERT's WordPiece. As BERT and its variants (e.g., RoBERTa) neglect the dependency between the masked positions and suffer from a pretrain-finetune discrepancy, XLNet adopts a permutation language model instead of masked language model to solve the discrepancy problem. For downstream tasks, the fine-tuning procedure of XLNet is similar to that of BERT and RoBERTa.

We use the BERT (base - 12 layers), RoBERTa and XLNet model implementations available from

the Hugging Face framework. The models were trained using the Adam optimiser [51] with an initial learning rate of $1.5e-5$, weight decay of 0.01, and early stopping with a patience of 5 epochs.

Combining model results

We use the RRF algorithm [52] to combine the results of different retrieval runs. RRF is a simple, yet powerful technique to re-score a retrieval list based on the scores of multiple retrieval lists. Given a set of documents D to be sorted and a set of ranking files $R=\{r_1...r_n\}$, each with a permutation on $1...|D|$, RRF computes the aggregated score using the following equation:

$$s(q,d,R)=\sum_{i=1}^{n}\frac{1}{k+r_i(q,d)},$$

where $r(q,d)$ is the rank of document d for the query q in the ranking file r_i and k is a threshold parameter, which was tuned to $k=60$ using data from previous rounds.

Second-step learning-to-rank

To exploit the features (relevance score) created by the different bag-of-words and masked language models, we added a second-step learning-to-rank pass to our pipeline. Using the similarity scores s computed by the BM25, DFR, LMD, BERT, RoBERTa and XLNet as input features and the relevance judgements of previous rounds as labels, we trained two learning-to-rank models: LambdaMART and a logistic regression classifier. While the language models exploit the sequential nature of text, they completely neglect the ranking provided by the bag-of-words models. Thus, we investigate the use of the LambdaMART [31] algorithm, which uses a pairwise loss that compares pairs of documents and tells which document is better in the given pair. Moreover, we trained a simple pointwise logistic regression to consider the similarity measures computed by the fist- and second-stage retrieval models. We used the pyltr and scikit-learn implementations for the LambdaMART and logistic regression, respectively. For the LambdaMART model we trained the learning rate and the number of estimators, and for the logistic regressions we trained the solver and regularization strength parameters.

First-stage retrieval: pre-processing, querying strategies and parameter tuning

In the first-stage retrieval step, we apply a classical NLP pre-processing pipeline to the publications (indexing phase) and topics (search phase): lower-casing, removal of non-alphanumerical characters (apart from "-"), and Porter stemming. Additionally, a minimal set of COVID-related synonyms, such as “covid-19” and “sars-cov-2”, were created and used for query expansion.

The queries are then submitted to the index in a combinatorial way using the different topic fields and document sections. This means that, for each of the *query*, *question* and *narrative* fields of a topic, we submit a query against the index for each of the *title* and *abstract* sections of the publications (*abstract* + *full text* in case of the full text index). Additionally, the whole topic (query + question + narrative) was queried against the whole document. This querying strategy leads to 7 queries for each topic and the final score is computed by summing up the individual scores. Moreover, as the first publicly announce of a coronavirus-related pneumonia was made in January 2020, we filter out all publications before December 2019.

We define the best query strategy and fine-tune the basic parameters of the bag-of-words models using the relevance judgements of the previous round in a 5-fold cross-validation approach. As an example, to tune the b and k parameters of the BM25 model at round 5, we take the topics and relevance judgement of round 4 and submit to the index of round 5, optimizing the P@10 metric. For round 1, we used default parameter values.

Evaluation criteria

We use the official metrics of the TREC-COVID challenge to report our results: precision at K documents (P@K), normalized discounted cumulative gain at K documents (NDCG@K), mean average precision (MAP) and binary preference (Bpref) [19]. For all these metrics, the closest to 1, the best is the retrieval model. They are obtained using the the *trec_eval* information retrieval evaluation toolkit.

Results

Seven models of our pipeline were used to create the 7 runs submitted for the official evaluation of the TREC-COVID challenge (labels M1 to M7 in (Figure 2)). Our first model - *bm25* - based on the BM25 weighting model against the metadata index provides the baseline run. Our second model - *bow + rrf* - is a fusion of the BM25, DFR and LMD weighting models computed against the metadata and full text indices and combined using the RRF algorithm. Model 3 - *mlm + rrf* - uses the RRF combination of BERT, RoBERTa and XLNet models applied to the top 5000 documents retrieved by model 2. Model 4 - *bow + mlm + rrf* - combines the results of model 2 and 3 using the RRF algorithm. Then, model 5 - *bow + mlm + lm* - re-ranks the results of runs 2 and 3 using the LambdaMART algorithm trained using the similarity scores of the individual models 2 and 3. Similarly, model 6 - *bow + mlm + lr* - is based on a logistic regression classifier that uses as features the similarity scores of runs 2 and 3 to classify the relevance of the query-document pairs. Finally, model 7 - *bow + mlm + lr + rrf* - combines runs 2, 3 and 6 using the RRF algorithm. For all RRF combinations, the parameter k was set to 60. All models and parameters were trained using round 4 relevance judgements. (Table 2) summarizes the submitted runs.

Table 2. Summary of the submitted runs. Refer to Figure 2 for a pictorial description.

run	name	description
1	bm25	Run based on the baseline BM25 model using the metadata index.
2	bow + rrf	An RRF combination of BM25, DFR and LMD models computed against the metadata and full text indices.
3	mlm + rrf	An RRF combination of BERT, RoBERTa and XLNet models applied to run 2.
4	bow + mlm + rrf	An RRF combination of runs 2 and 3.
5	bow + mlm + lm	A LambdaMART-based model using features from the individual models used to create runs 2 and 3.
6	bow + mlm + lr	A logistic regression model using features from the individual models used to create runs 2 and 3.
7	bow + mlm + lr + rrf	An RRF combination of runs 2, 3 and 6.

Official evaluation results

(Table 3) shows the official results of the TREC-COVID challenge for the 7 submitted runs. As we can see, the best results are provided by model 7 (bow + mlm + lr + rrf), apart from the metric Bpref, which is the highest for model 5 (bow + mlm + lm). Comparing the NDCG@20 metric, model 7 improved 16.4 percentage point against to the baseline model (26.0% of relative improvement). Overall, almost 17 out the top 20 documents retrieved by model 7 were pertinent to the query. Model 3 was able to retrieve 6.6% more relevant documents compared to the baseline model (6’963 *vs.*

6’533 out of a total of 10’910 documents judged relevant for the 50 queries). On the other hand, it showed a relative improvement in precision at the top 20 documents of 22.1%. Therefore, it not only improved the recall but also brought relevant documents higher in the ranking list. These results show that the use of the masked language models had a significant positive impact in the ranking.

Table 3. Performance of our models in round 5 of the TREC-COVID challenge. # rel is the total number of relevant documents retrieved by the model for the 50 queries. A total of 10910 documents were judged relevant by the organisers.

model	NDCG@20	P@20	Bpref	MAP	# rel
bm25	0.6320	0.6440	0.5021	0.2707	6533
bow + rrf	0.6475	0.6650	0.5174	0.2778	6695
mlm + rrf	0.7716	0.7880	0.5680	0.3468	6963
bow + mlm + rrf	0.7826	0.8050	0.5616	0.3719	7006
bow + mlm + lm	0.7297	0.7460	**0.5759**	0.3068	6834
bow + mlm + lr	0.7375	0.7450	0.5719	0.3439	6976
bow + mlm + lr + rrf	**0.7961**	**0.8260**	0.5659	**0.3789**	6939

(Table 4) shows the official best results for the different metrics for the top 10 teams participating in round 5 of TREC-COVID (NDCG@20 metric taken as reference). Comparing the NDCG@20 metric, the best model submitted by our team (risklick) was ranked 4 out of the 28 teams participating in round 5, 5.4 percentage point below the top performing team (Unique-ptr). For a reference, the best performing model in the challenge retrieves on average 17.5 relevant documents per query in the top 20 retrieved documents compared to 16.5 for our model. If we consider a reference baseline made by the median of the participating teams’ best value, our pipeline outperforms the baseline by 11.7%, 14.6%, 16.7% and 25.0% for the MAP, P@20, NDCG@20, and Bpref metrics, respectively. All data and results of the TREC-COVID challenge can be found at: https://ir.nist.gov/covidSubmit/data.html.

Table 4. Official leader board for the final round of the TREC-COVID challenge. Best results for the top 10 teams using the NDCG@20 as reference metric. A total of 28 teams participated in the TREC-COVID final round.

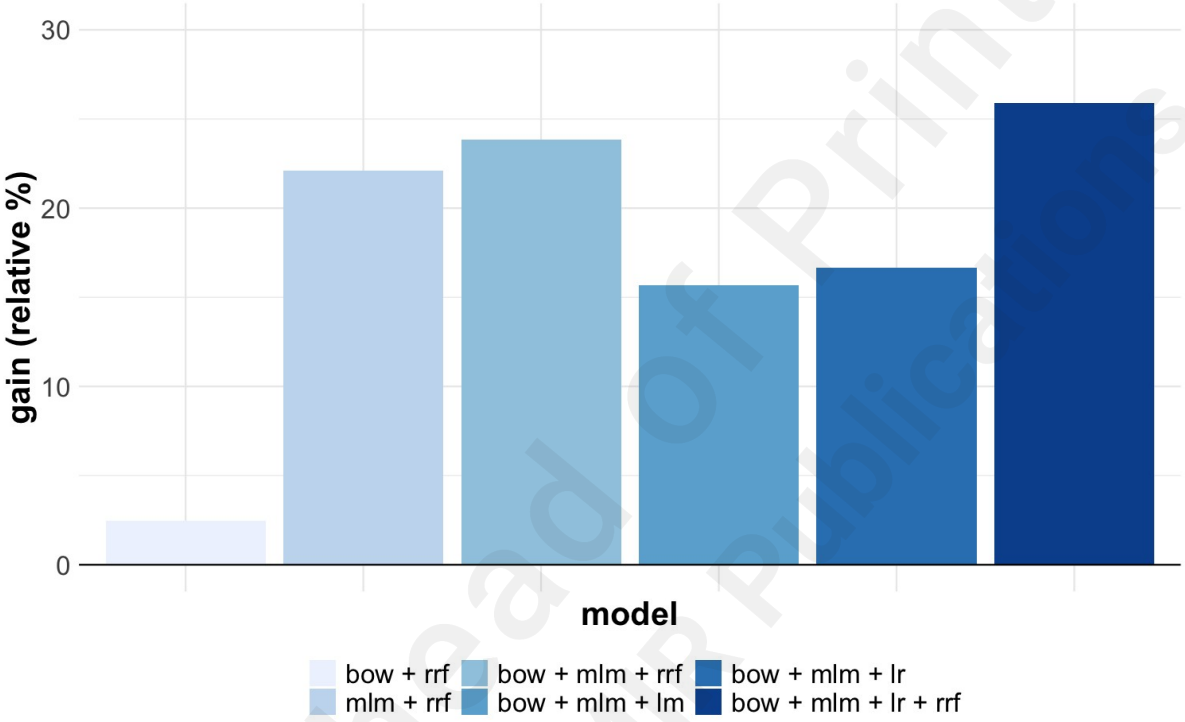
team	NDCG@20	P@20	Bpref	MAP
unique_ptr	0.8496	0.8760	0.6378	0.4731
covidex	0.8311	0.8460	0.5330	0.3922
Elhuyar_NLP_team	0.8100	0.8340	0.6284	0.4169
risklick (ours)	0.7961	0.8260	0.5759	0.3789
udel_fang	0.7930	0.8270	0.5555	0.3682
CIR	0.7921	0.8320	0.5735	0.3983
uogTr	0.7921	0.8420	0.5709	0.3901
UCD_CS	0.7859	0.8440	0.4488	0.3348
sabir	0.7789	0.8210	0.6078	0.4061
mpiid5	0.7759	0.8110	0.5873	0.3903

Model performance analyses

(Figure 4) shows the relative improvement of the different models in the pipeline in relation to the baseline (model 1 - bm25) according to the NDCG@20 metric. The most significant contribution to

the final performance comes from the inclusion of the masked language models in the pipeline - model 3 - mlm + rrf and model 4 - bow + mlm + rrf, adding a relative performance gain to the results of 22.1% and 23.8%, respectively. The classic learning-to-rank models - model 5 and model 6 - actually jeopardise the performance when compared to their previous model in the pipeline (model 4). However, when model 6 is combined with model 4, a 2.1 percentage point gain is achieved on top of model 4, leading to the best model (model 7 - bow + mlm + lr + rrf). Indeed, it is important to notice the consistent benefit of combining models using the RRF algorithm. Interestingly, the effect of LambdaMART seems to be significantly detrimental for *P*@20, *NDCG*@20 and *MAP*, but marginally beneficial for *Bpref*, for which it is the best model.

Figure 4. Relative contribution of each model for the *NDCG*@20 metric compared to the baseline model bm25.



The performance of the individual masked language models is shown in (Table 5). Surprisingly, they are similar to the baseline model, with small performance reductions for BERT and RoBERTa models, and a small performance gain for the XLNet model. However, when combined they provide the significant performance improvement shown in (Figure 4). Our assumption is that they retrieve different documents as relevant and their combination using RRF ends up aligning these documents in the top rank. Indeed, looking at the top 3 documents for query 1 retrieved by these models, for example, there is no overlap between the documents, being 8 relevant and 1 unjudged (out of the 9 documents). This result clearly shows the beneficial effect of using ensemble of masked language models, as well as the success of RRF in fusing their retrievals.

Table 5. Performance of the individual masked language models and their combination using RRF.

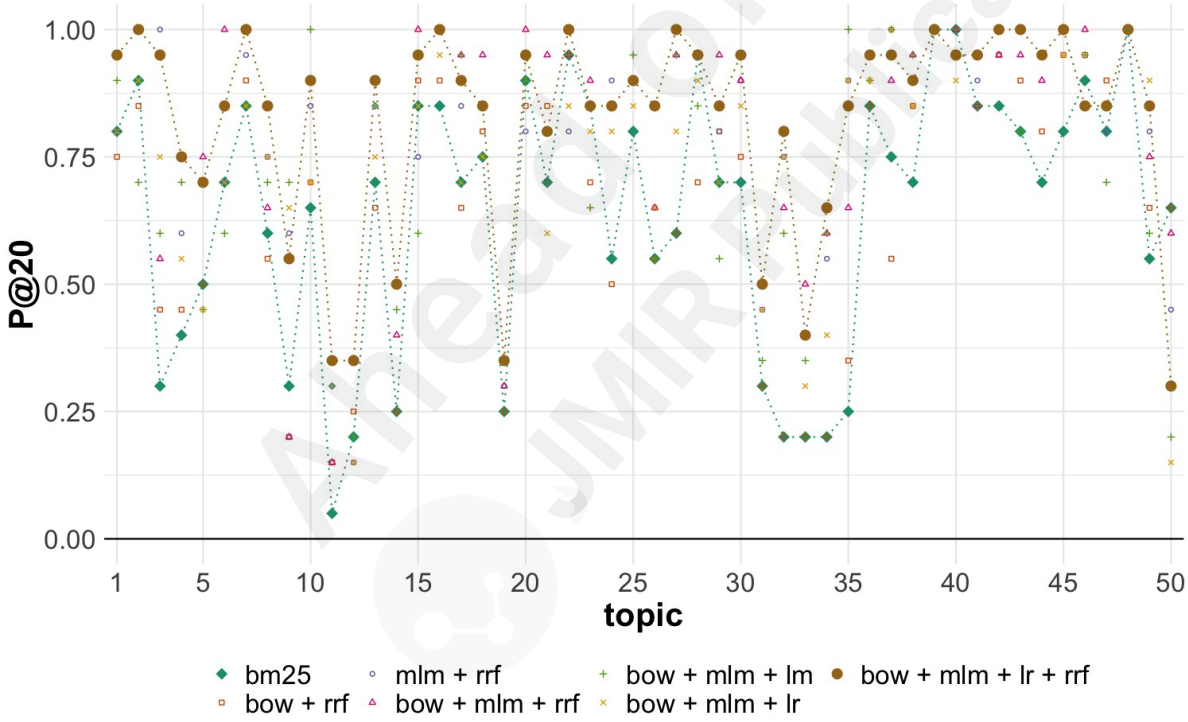
model	NDCG@20	P@20	Bpref	MAP	# rel
BERT	0.6209	0.6430	0.5588	0.2897	6879
RoBERTa	0.6261	0.6440	0.5530	0.2946	6945
XLNet	0.6436	0.6570	0.5644	0.3064	6926

mlm + rrf	0.7716	0.7880	0.5680	0.3468	6963

Topic performance analyses

The performance analyses for the individual topics shows that our best model has a median of 0.9000 for the P@20 metric (max=1.0000; min=0.3000), which demonstrates a successful overall performance. However, as shown in (Figure 5), for some topics, notably 11, 12, 19, 33, and 50, less than 50% of documents in the top 20 retrieved are relevant. For topics 11, 12, and 19, which searches for *coronavirus hospital rationing*, *coronavirus quarantine* and *what alcohol sanitizer kills coronavirus* information, respectively, all our models have a poor performance and indeed the combination of the different models in the pipeline manages to boost the results. On the other hand, for topics 33 and 50, which searches for *coronavirus vaccine candidates* and *mRNA vaccine coronavirus* information, respectively, it was the combination with the logistic regression model that lowered the performance (notice in (Figure 5) that model 4 - bow + mlm + rrf has a significantly better performance compared to model 7 for those queries).

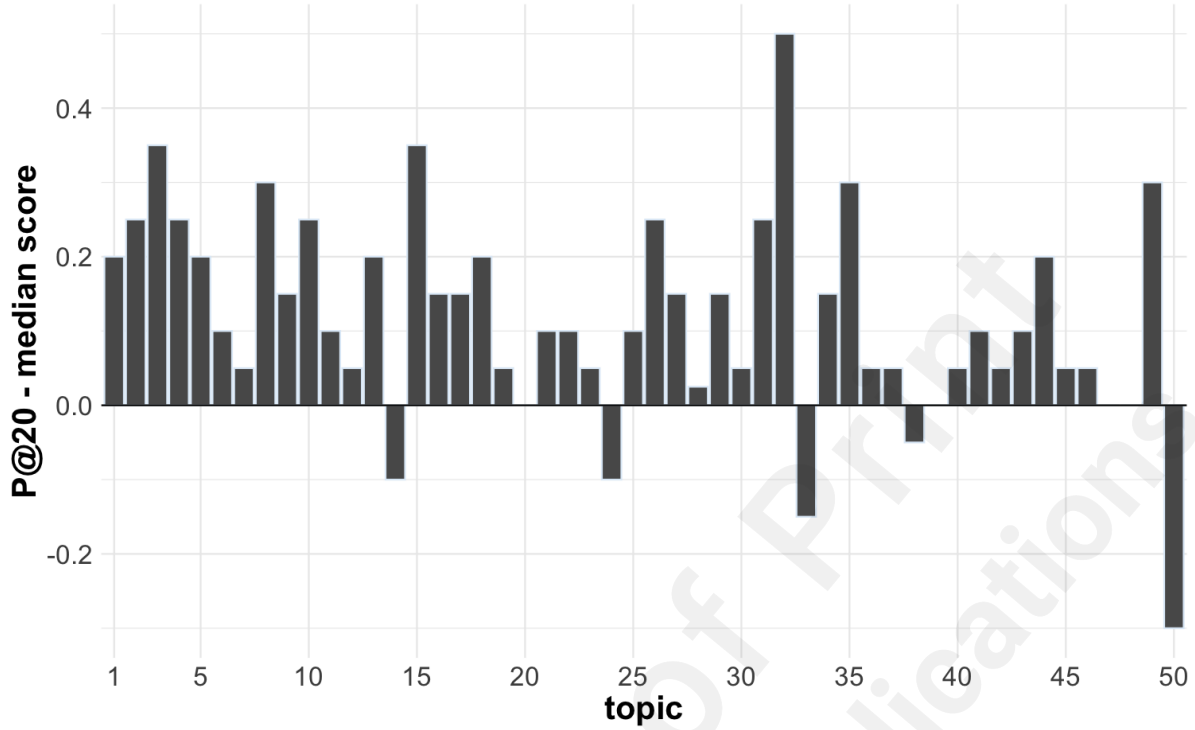
Figure 5. Per topic number of relevant publications retrieved up to rank 50 of round 5 of TREC-COVID per each run. The baseline run1 and the best-performing run7 which benefits from neural language models are highlighted with dashed lines. Note that for most topics, the transformer-based runs have significantly improved performance.



The difference in performance per topic between our best model and the median of the submitted runs in round 5 for all teams for the P@20 metric is shown in (Figure 6). Indeed, topics 11, 12, and 19 seem hard for all the models participating in the TREC-COVID challenge to retrieve the correct documents. Even if our best model has a poor performance for them, it still outperforms most of the runs submitted to the official evaluation. In particular, topic 19 has only 9 relevant or somewhat relevant documents in the official relevance judgements, which means that its max performance can be at most around 50% for the P@20 metric. For our worst performing topics compared to the other participants - topics 33 and 50 - a better tuning between the ranking weights of the bag-of-words,

masked language, and logistic regression models could have boosted the results.

Figure 6. Per topic performance difference between our best model (model 7) and the median of all official submissions for the P@20 metric in round 5.

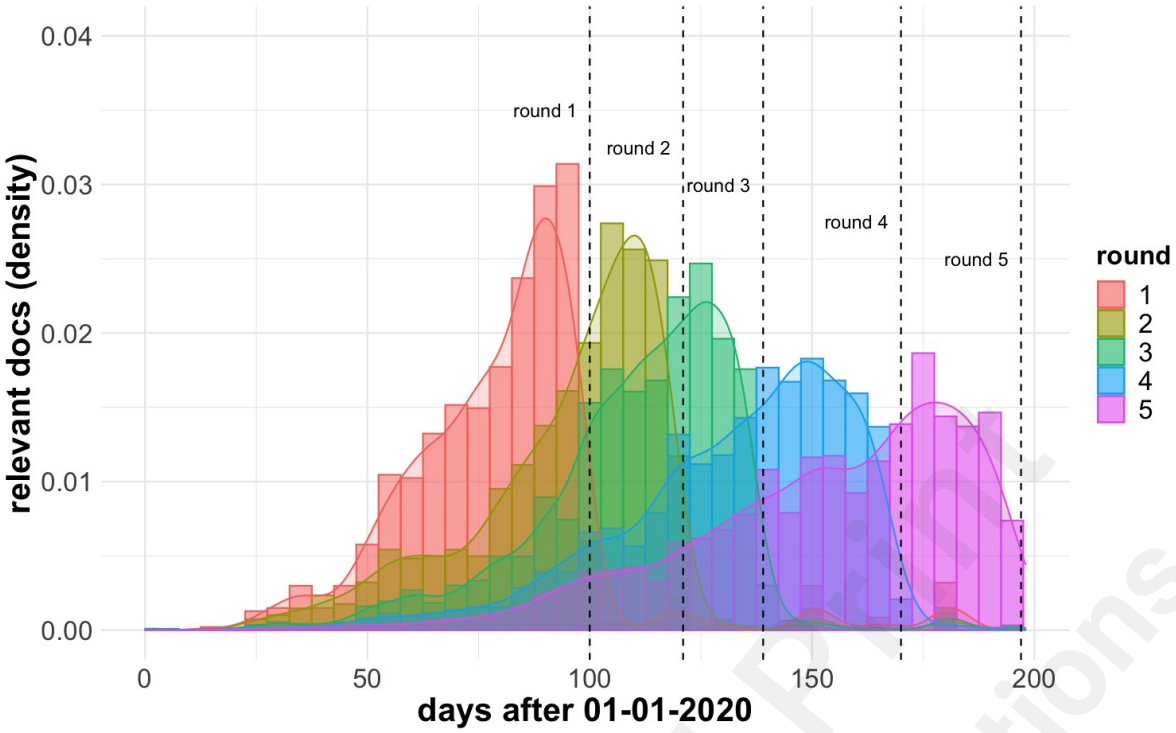


Time-dependent relevance analyses

Given the dynamics of the COVID-19 pandemics, with a starting period relatively well defined, a particularly effective technique to remove noise from the results, also adopted by some other participating teams [22], is filtering documents based on their publication dates. For our first-stage retrieval models, we filtered out publications before December 2019, when the outbreak was first detected. This led to a small negative impact on recall but highly improved the precision of our models.

To better understand how the document relevance varied over time, we analysed the publication date of the official relevance judgements for the five rounds of TREC-COVID. As we can see in (Figure 7), there is a clear exponential decay pattern in the number of relevant articles over time for all the rounds, with a faster decay in the first rounds and a longer tail for the later ones. We notice that more recent publications, closer to round start when the snapshot of the collection was created and queries were submitted, tend to have a higher probability of being relevant to the information need, with a half-life of around 20 days for round 1. This is somehow expected as the documents found in previous query rounds were explored and are no longer relevant, only the most recent data is interesting, particularly in the gap between rounds. A second explanation is that in the case of a pandemic, new evidence arrives with an explosive rate, possibly refuting older knowledge.

Figure 7. Distribution of the publication dates of the “highly relevant” articles for each of the TREC-COVID rounds.



Discussion

To support effective search and discovery of COVID-19-related relevant literature in the COVID-19 infodemic, we explored the use of a multi-stage retrieval pipeline supported by bag-of-words models, masked language models and classic learning-to-rank methods. The proposed methodology was evaluated in the context of the TREC-COVID challenge and achieved competitive results, being ranked top 4 out of 126 runs from 28 teams participating in the challenge. The use of the multi-stage retrieval approach significantly improved the search results of COVID-related literature, leading to a gain in performance of 25.9% in terms of the NDCG@20 metric compared to a bag-of-words baseline. Particularly, the ensemble of masked language models brought the highest performance gain to the search pipeline. Indeed, ensembles of language models have proved to be a robust methodology to improve predictive performance [53–55].

The COVID-19 pandemic has led to a huge amount of literature being published in most diverse sources, including scientific journals, grey repositories, white reports, among others. As the pandemic continues, the number of scientific publications grows at an unprecedented rate causing an infodemic within many different disciplines involved [3]. Finding the most relevant information sources to answer different information needs within the huge volume of data created had become of utmost necessity [2]. By enabling the discovery of relevant information sources to complex user queries, effective retrieval models as proposed in this work may help to tackle the spread of misinformation. Such models empower experts with a minimal cost to search and discovery information sources within a massive and fast evolving corpus. Indeed, our model provides relevant information sources for more than 8 documents in the top-10 rank. Thus, continuous active search methods could be put in place to monitor and timely discover sources of evidence to certain query topics of relevant public health interest, e.g., “coronavirus origin”. This in turn would enable experts to analyse, identify and curate both sources of best evidence at the time and sources of misinformation. The former would foster the creation among others of living systematic reviews [56,57], which is one of the recommendations of the WHO to tackle the COVID infodemic [2]. On the other hand, the latter could help fighting, for example, the spread of scientific fake news by early

retraction of misinforming articles, particularly in pre-prints servers, and thus limiting their exposition.

Looking at the boost in performance of model 3 alone, one could be tempted to argue that masked language models could be the main component in a retrieval system. However, two issues may arise: algorithmic complexity and search effectiveness. The former is related to the high complexity of masked language models ($O(n^2 \cdot h)$, where n is the sentence length and h is the number of attention heads), which makes it prohibitive to classify a whole collection, often containing millions of documents, for every given query. The latter is related to the effectiveness of the individual models themselves. As shown in (Table 5), individually the performance of the language models is not significantly different from the baseline BM25 model. Thus, we believe it is the combination of models with different properties that can provide a successful search strategy in complex corpora, as the one originated from the COVID-19 infodemic.

In terms of practical implications, by effectively processing natural language the methodology proposed can help biomedical researchers and clinicians to find the COVID-19 papers that they need. The efficient literature discovery process fostered by our methods may lead to faster publication cycles when required, for example reducing from weeks to days the drafting time of COVID-19 reviews [58], but also to less costly creation of curated living evidence portals, which will inform clinicians and public health officers with the best available evidence [59]. Indeed, as shown in [27,60], these methodologies outperform commercially available tools for searching and discovering COVID-19 related literature. Moreover, as they are data-driven, it is expected that they can be extrapolated to other types of corpora, such as clinical trial protocols and biomedical metadata datasets [60,61], enabling thus a more comprehensive identification of scientific evidence. Equally important, as the COVID-19 infodemic is not the first and unlikely the last [62,63], our methodology and findings could be extended to help tackling future epi-, pan- and info-demics by supporting relevant actors to scan large and fast changing collections to create timely reviews and curated evidence, and apply localized infodemic management approaches.

With the rapid surge of published information, and the variety of topics and sources related to COVID-19, it became hard for professionals dealing with the pandemic to find the correct information for their needs. While the automation discussed in this work can support more effective search and discovery, some high-level topics are still challenging. Indeed, some topics assessed in the TREC-COVID challenge showed to be particularly hard to the retrieval models. For example, for topic 11, which searched for documents providing information on “guidelines for triaging patients infected with coronavirus", our best model prioritized documents providing information about indicators for diagnosis (“early recognition of coronavirus", “RT-PCR testing of SARS-CoV-2 for hospitalized patients clinically diagnosed", etc.). On the other hand, it missed documents including passages such as “telephone triage of patients with respiratory complaints". Similarly, for topic 12, which searched information about the “best practices in hospitals and at home in maintaining quarantine", our model prioritized documents providing information about “hospital preparedness" (“improving preparedness for", “preparedness among hospitals", etc.) and missed documents containing information about “home-based exercise note in Covid-19 quarantine situation".

The methodology proposed has some limitations. First, it fails to explore transfer learning of learning-to-rank datasets. While the top-rank teams all used multi-stage retrieval approaches confirming the value of such methodology in modern retrieval models [18,23], the re-ranking strategy within the different pipelines varied slightly among the participants. For example, the top-1 team used transfer learning from the MS MARCO learning-to-rank dataset and from a zero-shot learning approach. Other teams in the top-3 used transfer learning from a silver collection, based on

the known item search technique [64]. Second, while we explored the combination of different topic items to build our queries, we fail to work on the document indexing unit, leaving all the normalisation work to the probabilistic weighting models. As the COVID-19 literature comes from heterogeneous collections, containing sometimes only title and sometimes large full text, even with good finetuning of the model parameters, such variation in size and content poses a challenge to the first-stage retrieval model. Indeed, some strategies that explored decomposing the indexing unit into small structures, such as sentences and paragraphs, have achieved more competitive results [23].

Another limitation of our work was to explore the freshness of the corpus. The TREC-COVID challenge dynamics, running throughout a sequence of rounds with new incremental search topics added on each round provides an interesting setting for evaluating retrieval models in an infodemic context. It simulates typical search and discovery workflows, in which evolving queries are posed against an evolving body of knowledge over time, and already discovered documents in previous searches are no longer relevant [65,66]. A successful strategy in this case is to filter out results according to a cut-off date, reducing thus noise in the retrieval set. However, in retrospect, we notice that another useful technique, which is very natural to an infodemic case, could be to decay the score of publications by their distance to the present time or explore their recency or freshness [67,68], as highlighted in (Figure 7), rather than a hard cut-off (i.e., December 2019 in our case) for all the rounds. We leave exploring such strategy as future work.

To conclude, we believe our information retrieval pipeline can provide a potential solution to help researchers, decision makers, and medical doctors, among others, search and find the correct information in the unique situation caused by the COVID-19 pandemic. We detailed the different components of this pipeline, including the traditional index-based information retrieval methods, the modern NLP-based neural network models, as well as insights and practical recipes to increase the quality of information retrieval of scientific publications targeted to the case of an infodemic. We grounded our results to the TREC-COVID challenge, where around 50 different teams participated in 5 rounds of competition. We showed very competitive results as judged by the official leader board of the challenge. Apart from the COVID-19 case, we believe our solutions can also be useful for other potential future infodemics.

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Author contributions statement

D.T. conceived the experiments, D.T. and S.F. conducted the experiments, D.T., S.F., E.K. and P.A. analysed the results. N.B., E.K., D.V.A and P.A. prepared the data, S.F., D.T., J.C., R.G. and N.N. drafted the manuscript. All authors reviewed the manuscript.

Conflicts of Interest

P.A. and N.B. work for Risklick AG (www.risklick.ch). The other authors declare no competing interests.

Abbreviations

CORD-19: COVID-19 Open Research Dataset
NLP: natural language processing

BERT: Bidirectional Encoder Representations from Transformers
BM25: Okapi Best Match 25
DFR: Divergence from Randomness
LMD: Language Model Dirichlet
tf-idf: term frequency-inverse document frequency
NDCG: normalized discounted cumulative gain
MAP: mean average precision
Bpref: binary preference

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